CNN-Based Detection of Pneumothorax and Effusion in Chest X-Rays

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Abstract

This project presents a convolutional neural network (CNN)-based classification model for thoracic diseases using chest X-rays from the NIH ChestX-ray14 dataset. Following initial challenges with 20 disease classes, the study was narrowed to Pneumothorax and Effusion, as these conditions exhibit clearer radiographic patterns. The final model, implemented in MATLAB, achieved an accuracy of 75% for Pneumothorax and 65% for Effusion. These results highlight the potential of AI in radiology while emphasizing the importance of expert input, artifact-free datasets, and rigorous clinical validation.

Introduction

Misdiagnosis of thoracic conditions is common in clinical radiology, often due to overlapping anatomical structures and subtle findings in chest X-rays. Such limitations can delay treatment or lead to inappropriate management. Deep learning, particularly convolutional neural networks (CNNs), offers a promising approach to enhance diagnostic accuracy by identifying complex visual patterns. This project investigates a CNN-based model trained on chest X-rays from the NIH ChestX-ray14 dataset. Following inconsistent results across multiple disease classes, the study was narrowed to Pneumothorax and Effusion, two conditions with clearer radiographic features that enabled more stable model performance.

Objectives

I. Develop a convolutional neural network (CNN) model to assist in the classification of thoracic diseases using chest X-rays.

II. Address common diagnostic errors resulting from subtle findings and overlapping anatomical structures.

III. Focus on Pneumothorax and Effusion, which present more distinct radiographic patterns.

IV. Enhance model performance through targeted image preprocessing and class selection.

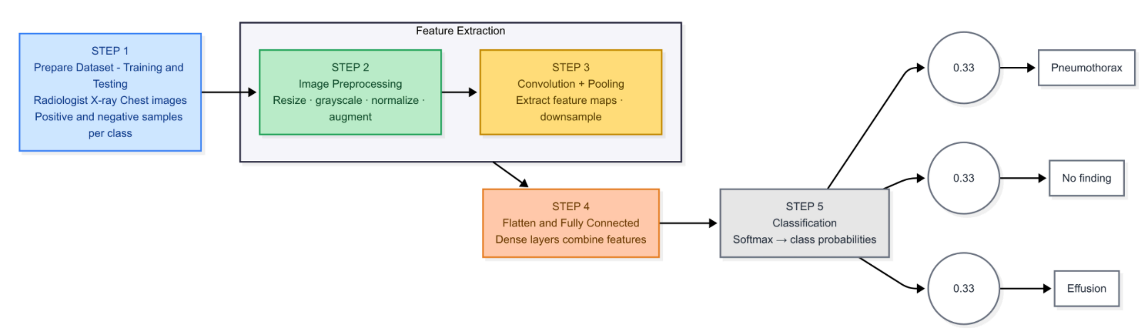
V. Evaluate accuracy and identify both technical and clinical limitations.

Methodology

Pneumothorax

Effusion

Training Process



1. Dataset Selection

I. Source: NIH ChestX-ray14 dataset (>100,000 frontal chest X-ray images).

II. Two binary classification tasks:

a. Pneumothorax vs. No Finding

b. Effusion vs. No Finding

III. Balanced datasets with an equal number of positive and negative samples for each task.

2. Image Preprocessing

I. Images maintained at original resolution (1024×1024).

II. Converted to grayscale and normalized pixel values.

III. No removal of annotations, text, or artifacts.

3. CNN Architecture

I. Conv Layer 1: 16 filters (3×3), ReLU, MaxPooling (2×2)

II. Conv Layer 2: 32 filters (3×3), ReLU, MaxPooling

III. Conv Layer 3: 64 filters (3×3), ReLU, MaxPooling

IV. Flatten → Dense (128 neurons, Dropout 0.5) → Dense (64 neurons) → Output (Softmax)

4. Training Configuration

I. Optimizer: Stochastic Gradient Descent (SGD)

II. Loss Function: Cross-Entropy

III. Batch size: 32, Epochs: 30

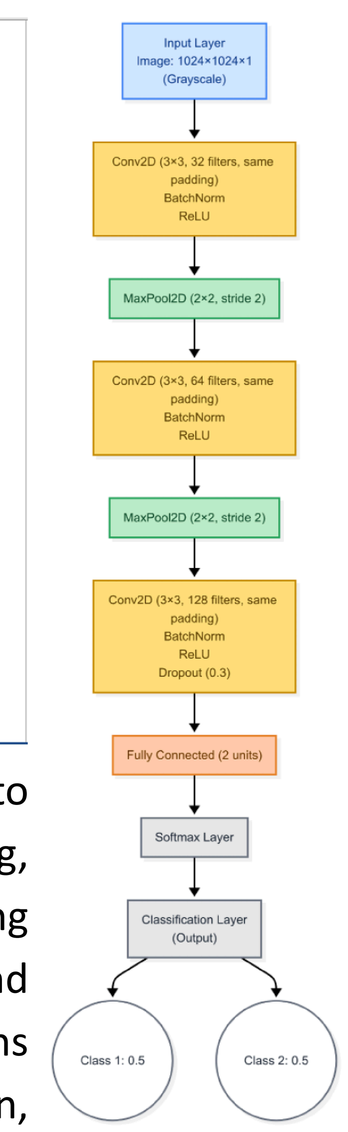
IV. Separate training for each classification task

V. No explicit validation or testing phase performed

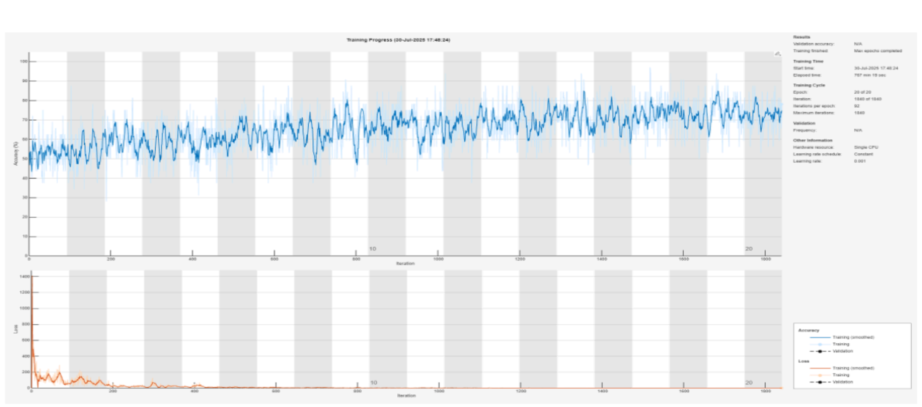
Network Architecture

MATLAB

```
load('CNN_Effusion_Data.mat'); % Variables: Data, Labels
fprintf('Data loaded..\n')
% Augmentación de datos (mejora la generalización)
imageAugmenter = imageDataAugmenter( ...
    'RandRotation', [-10,10], ...
    'RandXTranslation', [-5,5], ...
    'RandYTranslation', [-5,5]);

augimdsTrain = augmentedImageDatastore([1024 1024], Data, Labels, ...
    'DataAugmentation', imageAugmenter);

% Definición de arquitectura robusta
layers = [
    imageInputLayer([1024 1024 1], 'Name', 'input')

    convolution2dLayer(3, 32, 'Padding', 'same', 'Name', 'conv1')
    batchNormalizationLayer('Name', 'bn1')
    reluLayer('Name', 'relu1')
    maxPooling2dLayer(2, 'Stride', 2, 'Name', 'maxpool1')

    convolution2dLayer(3, 64, 'Padding', 'same', 'Name', 'conv2')
    batchNormalizationLayer('Name', 'bn2')
    reluLayer('Name', 'relu2')
    maxPooling2dLayer(2, 'Stride', 2, 'Name', 'maxpool2')

    convolution2dLayer(3, 128, 'Padding', 'same', 'Name', 'conv3')
    batchNormalizationLayer('Name', 'bn3')
    reluLayer('Name', 'relu3')
    dropoutLayer(0.3, 'Name', 'dropout')

    fullyConnectedLayer(2, 'Name', 'fc')
    softmaxLayer('Name', 'softmax')
    classificationLayer('Name', 'output')
];

% Opciones de entrenamiento sin validación
```



MATLAB was selected for this project due to its powerful integration of image processing, machine learning, and deep learning toolboxes, enabling rapid prototyping and streamlined workflows. Its built-in functions simplify data augmentation, network design, and training management, making it ideal for medical imaging tasks where precision, reproducibility, and ease of experimentation are essential.



This figure illustrates the training progress of the CNN for chest X-ray classification over 20 epochs and 1,840 iterations. Training accuracy (blue) increased steadily from ~55% to 70%, while training loss (orange) dropped rapidly in the initial iterations and stabilized near zero, indicating convergence. No validation accuracy was reported since all available data was used for training. The experiment was executed on a single GPU with a constant learning rate of 0.001, demonstrating the model's ability to learn under limitedcomputational resources.

Analysis and Results

The Pneumothorax classification model achieved an accuracy of 75%, while the Effusion model reached 65%. These results align with the performance range reported in similar studies without transfer learning, typically between 65% and 85% accuracy. Several factors may have limited model performance, including the absence of radiologist input to verify image labels, the presence of visual artifacts such as annotations and grid lines, and potential inconsistencies within the dataset. Despite these limitations, the findings indicate that convolutional neural networks can detect certain thoracic diseases with moderate accuracy, even when trained on unfiltered images.

Conclusion

Findings from this study demonstrate that convolutional neural networks can classify Pneumothorax and Effusion from chest X-rays with moderate accuracy, even when trained on unfiltered images. Reported accuracies in similar studies using datasets such as NIH ChestX-ray14 and CheXpert range from 65% to 85%, including those with advanced architectures like DenseNet, supporting the validity of our results. Nevertheless, clinical guidance and enhanced preprocessing are crucial for improving performance. Future work should prioritize collaboration with radiologists for dataset validation, removal of annotations and artifacts, image resizing to optimize memory usage, and increased GPU memory capacity, as limited hardware resources impacted this investigation.

Acknowledgements

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